An unsupervised Random Walk algorithm in Image Segmentation

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Random Walk is an efficient method in Image Segmentation. When we have enough useful seeds. It's fast and accurate. But its drawback is that these seeds need human to find out. In this project, I try to show a unsupervised method of Random Walk. And shows it is efficient to some kind of images.

1 Introduction

Random Walk algorithm in image segmentation was first proposed by *Leo Grady*. This algorithm using the seeds and labels given by human. Calculate each pixels' probabilities to each label. Found the biggest probability, and decide which label does the pixel belong. In this algorithm. The selection of the seeds and labels are very important. Accurate seeds will make a good result. But if there's no one to pick up the optimal seeds. How can this algorithm work. Here provides a method to find the seeds based on the gray of image.

2 Background

Image segmentation is a process of partitioning an image into multiple parts or regions with similar features or properties. This section will introduce *Grady's* Random Walk algorithm. The algorithm can conclude as follow:

1.Giving the seeds and labels.

2.Getting image and generate an undirected graph $G =< V, E >$.

3.Generate Laplacian Matrix L.

4.Depend on the boundary condition and solve the probability that the seeds first arrive each nodes.

5.Segregate the image depend on the probability.

2.1 Generate Undirected Graph

Graph-based segmentation methods model an image I as a weighted undirected graph $G =< V, E >$ for input image $I(v)$, Where the nodes V represent the image pixels. And E represent the neighbourhood pixels.**[2]**

2.2 Generate Laplacian Matrix

Laplacian Matrix L is a $m \times m$ matrix where m is the number of node V. When the scale of image is large. Its Laplacian Matrix is larger. Because most element of L is 0. It can be dealt as a sparse matrix.

$$L_{ij} = \begin{cases} d_i & if \quad i = j \\ -w_{ij} & if\ v_i\ and\ v_j\ are\ adjacent\ nodes \\ 0 & otherwise \end{cases}$$

Where w_{ij} is the edge weight between v_i and v_j.

$$w_{ij} = exp(-\beta J((v_i) - J(v_j))).$$

$$d_i = \textstyle\sum_j w_{ij}.$$

In this project $J(v_i)$ represent the gray level of v_i.

2.3 Solve the probability

In *Grady's* algorithm, Laplacian matrix L can partitioned as

$$\begin{bmatrix} L_M & B \\ B & L_U \end{bmatrix}$$

Where B represent the boundary. L_M represent seeded nodes and L_U represent unseeded nodes.

The optimal solution of the problem is

$$L_u p_{ui}^{lk} = -B^T p_{mi}^{lk}$$

p_{ui}^{lk} represent the probability of node u_i in label l_k.

And then, using the probability to decide which label does the node belong.

Fig 1 is an example given by *Grady*. Picture(a) is the decision of segmentation. Picture(a),(b),(c) is the probability that each node belong to Label L_1, L_2, L_3. The decision is segment each node to its most likely label.

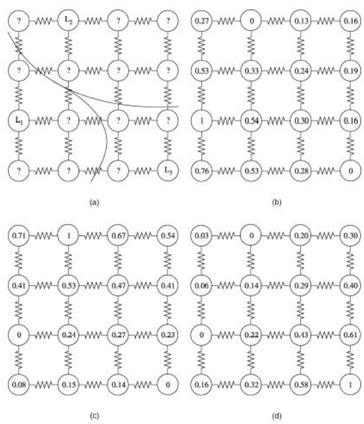

Figure 1. An example given by Grady.

3 Find optimal seeds

In *Grady's* algorithm, there're some conditions to have a good performance:

> *1.Enough and accurate seeds.(If the number of seeds is small, it will affect the accuracy. If the number is large ,it will cause much calculation).*
>
> *2.The image shouldn't be complicated.(This algorithm doesn't suit to complex images. Because a complex picture may have many label and complex properties. But a complicated image can separate into simple images or using some filter to simplify it.)*

In the algorithm, finding the seeds is important. If we don't give the seeds by human. How can we use the characteristic of images to predict the seeds.

3.1 Estimate seeds condition on the grey-scale

Firstly, I consider about the gray level. It's a characteristic that easy to get and useful. The histogram of an image H.Always can separate into serval part that :

$$H = [h_1, h_2 ... h_n], \qquad (n \geq 2)$$

Intuitively, we can select seeds with grey level belong to $h_1, h_2..., h_n$. And label them as $l_1, l_2..., l_n$.

Before deciding the separation. A moving average is needed to reduce the noise.

In example 1 the image's histogram can be divided by 35,135,183. And then, we can sample some seeds belong to each grey level randomly.(With probability 1/16). Here's the result in Figure4.

Figure 2. example 1

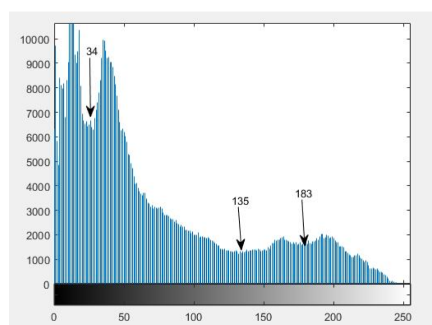

Figure 3. separation of histogram

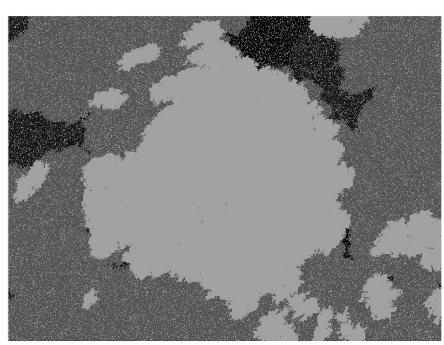

Figure 4. first segmentation of example 1

3.2 Estimate the seeds though the outline

In this segmentation, we can see the approximately outline of the image. But this segmentation is not accuracy.Because in the optimal algorithm seeds should be chosen accurate.But in this segmentation, we chosen the seeds randomly. Which cause the seeds belong to different label may located so close. And this will blur the ownership of some area which influenced the algorithm's accuracy. But the result still provide the information of outline.

Now we have kind of the prior distribution of the seeds. In Figure 5, there's the outline. For example, in the area $Label1$, it's more likely chosen the nodes as seeds in $Label1$, Similarly if in the area $Label2$, there's a strong belief to label the seeds in $Label2$...

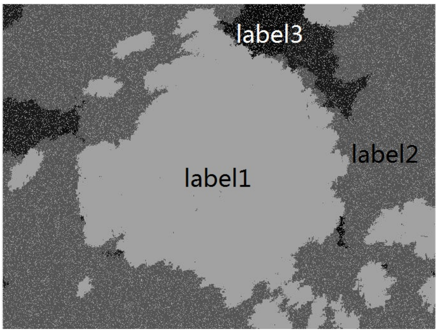

Figure 5. approximately outline of example 1

To achieve this goal. Here's my solution:

1. *Randomly select a node v_{ij} as a seed(Because the seeds this time are more effective,so the number of the seeds can be much lesser to reduce the calculation).*

2. *Using the previous result, decide which label does it belong.*

3. *Segregate the image by the new seeds.*

Here's a simply method to decide the new seed:

let $L = (L_{i,j} + L_{i+1,j} + L_{i-1,j} + L_{i,j-1} + L_{i,j+1})/5$.

The label $L'_{i,j} = [\textit{The label most closed to L}]$

This method works because it reduces the invalid seeds. For example, node v_{ij} was first ranged as $Label1$, but if its adjacent nodes were ranged as $Label2$. That v_{ij} is likely invalid. And in this method it will be ranged as $Label2$ in new seeds.

There's the result in Fig.6 of example1 with new seeds:

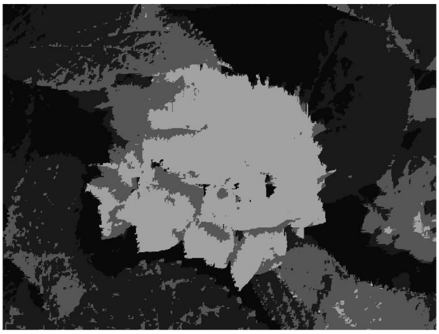

Figure 6. result of example 1 with new seeds

In this result the segmentation are more accurate.

4 Result and analysis

Here's the completed optimised algorithm:

Input image I and generate undirected graph $G =< V, E >$.

Generate histogram H of I and separate it to $h_1, h_2, ...h_n$ by minimum value.

Decide labels $L_1, L_2, ...L_n$ though $h_1, h_2, ...h_n$.

Randomly choose seed sets $S_1, S_2, ...S_n$ in grey level $h_1, h_2, ...h_n$.

Generate Laplacian matrix L and calculate the probability and decide the segmentation M.

Using the information of M and choose new seed sets $S'_1, S'_2, ...S'_n$.

Generate new segmentation $\overline{M}$ by seeds $S'_1, S'_2, ...S'_n$ and labels $L_1, L_2, ...L_n$.

There are some result:

During the result, the algorithm perform well in color and shape. If merge those small area into big's, It will perform better. But it still has some drawbacks. First, it doesn't work well when the image is complex. Image (c) is a bit complex and the algorithm doesn't deal it well.

And there's a big problem that the algorithm is base on the color(A computer vision).It can't figure out that the deep blue and blue part should both belong to label 'sea'(In image(a)), white and blue part should belong to label 'sky'(In image (b)), the yellow part and the shadow should both belong to the label 'flower'(In image (c)).

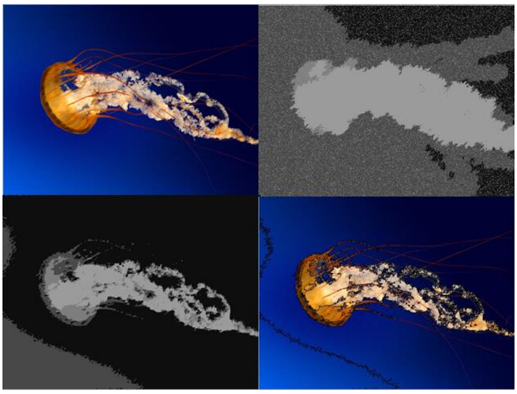

Figure 7. (a)

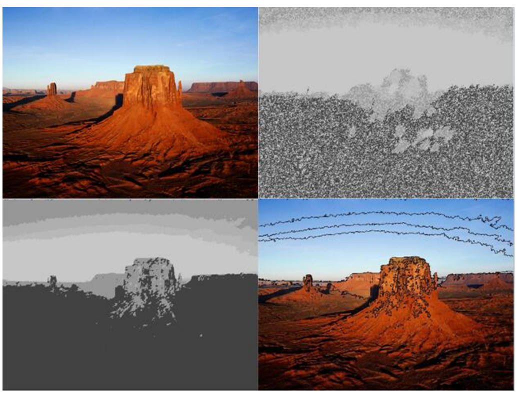

Figure 8. (b)

Because grey levels of blue and deep blue are different. This algorithm will treat them as different labels.We should tell the computer they are the same thing, maybe a information of edge is useful. Introducing other segmentation methods like edge based segmentation may help solve the problem in (a),(b).The more kinds of information we use, the more accurate the result will be. But how to balance the weights of each method,it still a problems. Maybe machine learning with big data will give a optimal way.

Come to the problem in (c),using other color space like HSV may help.

Conclusion

In the project, I reproduce *Leo Grady*'s random walk algorithm. And introduce an unsupervised algorithm based on it. Optimize the algorithm and do some test and analysis the result. And plan to do some further work to make it better.

Figure 9. (c)

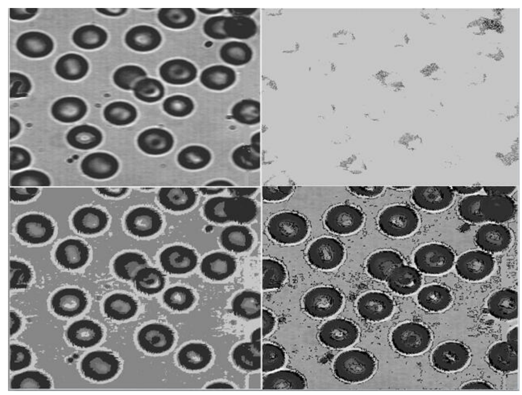

Figure 10. (d)

References

[1] L. Grady, Random walks for image segmentation, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 11, pp. 1768C1783, Nov. 2006.

[2] Tayebeh Lotfi Mahyari; Richard M. Dansereau ”Learning-Based multilabel random walks for image segmentation containing translucent overlapped objects” International Conference on Telecommunications and Signal Processing (TSP),pp. 610 - 614, 2017

[3] Wang fuzhi;Qin fujun;Jiang daijun;Song changlin, ’andom walks for image segmentation based on visual attention’, Chinese Journal of Scientific Instrument, vol. 38,no. 7, pp. 214–222, July.2017